How to Build the Best Macroscopic Description of your Multi-agent System? Application to News Analysis of International Relations

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Application to News Analysis of International Relations

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Abstract

The design and debugging of large-scale MAS require abstraction tools in order to work at a macroscopic level of description. Agent aggregation provides such abstractions by reducing the microscopic description complexity. Since it leads to an information loss, such a key process may be extremely harmful if poorly executed. This research report presents measures inherited from information theory (Kullback-Leibler divergence and Shannon entropy) to evaluate abstractions and to provide the experts with feedbacks regarding the generated descriptions. Several evaluation techniques are applied to the spatial aggregation of an agent-based model of international relations. The information from on-line newspapers constitutes a complex microscopic description of agent states. Our approach is able to evaluate geographical abstractions used by experts and to deliver them with efficient and meaningful macroscopic descriptions of the world state.

Keywords: Large-scale multi-agent systems, agent aggregation, macroscopic description, information theory, geographical and news analysis.

1 Introduction

Because of their increasing size, complexity and concurrency, on-going multi-agent systems (MAS) can no longer be understood from a microscopic point of view. Design, debugging and optimization of such large-scale distributed applications need tools that proceed at a higher level, with insightful abstractions regarding the system global dynamics. Among abstraction techniques (dimension reduction, subsetting, segmentation, clustering, and so on [4]), this research report focus on *data aggregation*. It consists in losing some information about the agent level to build simpler yet meaningful macroscopic descriptions. Such a process is not harmless and an unfortunate aggregation can lead to a critical misunderstanding of the MAS behavior. Hence, we have to determine what are *good* abstractions and how to properly use them. At each stage of a MAS development, aggregation process should be carefully monitored and feedbacks should be provided regarding the quality of generated macroscopic descriptions.

A simple example can demonstrate how critical an aggregation can be. Fig. 1 shows two groups of agents (on the left) that may be simplified by two abstract entities with an average behavior. Intuitively, group A constitutes a *good* abstraction since the induced global behavior is relatively similar to the microscopic one, unlike for group B. Hence, aggregation of redundant information should be encouraged to reduce the description complexity (group A), but heterogeneous behaviors should be kept detailed to control the information loss (group B).

Very few work have been done in the MAS community to estimate such aggregation properties. The main contribution of this report consists in introducing measures from information theory (Kullback-Leibler

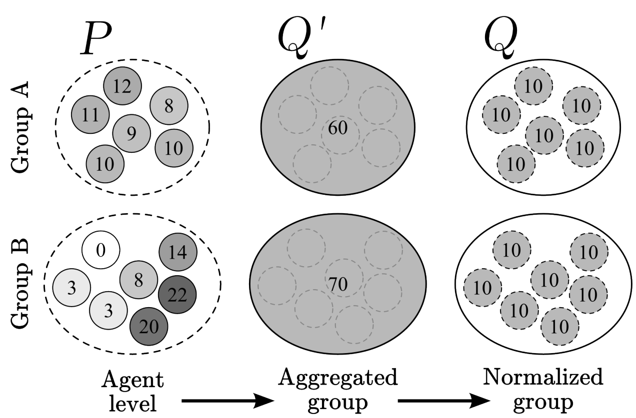


Figure 1: The simplification of a group of agents by an average behavior may reduce redundant information (group A) or it may lead to an unwanted information losses (group B).

divergence [8] and Shannon entropy [13]) to defined what is a *good* aggregation. We provide these measures with generic feedback techniques and with an algorithm that build multi-resolution descriptions out of hierarchically organized MAS. These techniques and algorithms are applied to the agent-based modeling of international relations: agents are countries, and their behavior is extracted from 70 on-line newspapers. Geographers are used to exploit multi-level aggregates to build statistics regarding world areas. We show how such geographical abstractions should be chosen to better understand the system dynamics. This ambitious GEOMEDIA project is conducted in collaboration with geography and media experts from the CIST (*Collège International des Sciences du Territoire*, Paris).

Section 2 presents the work related to the main concern of this article. Section 3 presents the agent-based model of the GEOMEDIA application. Section 4 introduces KL divergence to estimate *information loss* and section 5 Shannon entropy to estimate *complexity reduction*. Section 6 shows how these measures can be combined to identify *best aggregations* and to build multi-resolution descriptions. Section 7 concludes this report and gives some perspectives.

2 Related Work

Aggregation can take place in every stage of a MAS development: from its design to its use. Even if abstraction techniques may differ from one stage to an other, each one should carefully take into consideration the aggregations quality. First, on a software perspective, this section shows that very few research efforts have been done to consistently respond to this matter, in agent-based simulation platforms, trace monitoring systems, and also outside of the MAS domain. (1) Most classical platforms do not even provide the user with abstraction tools; (2) some do handle the issue, but are still at an early stage of thought. Secondly, on a theoretical aspect, this section explains why classical techniques (*e.g.* data clustering and graph analysis) are not entirely satisfying to build meaningful abstractions. Our approach should rather be compared to recent work in multi-level MAS [5] to which it may provide a formal and quantitative framework.

In a comprehensive survey of agent-based simulation platforms [12], Railsback *et al.* evaluate simulation tools by implementing classical features of MAS modeling and analysis. Unfortunately, the abstraction problem is not tackled, thus indicating that such considerations are seldom if ever taken into account. Indeed, most platforms (Java Swarm, Repast, MASON, NetLogo and Objective-C Swarm) are confined to the microscopic simulation of agents. Railsback warns against the lake of "a complete tool for statistical output" in these platforms. The provision of global views on the MAS macroscopic behavior thus constitutes a on-going research topic. Some tools for large-scale MAS monitoring however address this issue. For example, in some debugging systems, abstractions are used to reduce the information complexity of execution traces. However, these abstractions are either limited to the simplification of agents internal behavior, and do not tackled multi-agent organizational patterns [17], or they do not provide feedbacks regarding the quality of such abstractions [1]. In the ASGARD monitoring system [15], the level of detail is grounded on the distance between the observer and the agents in a 3D space. Such a visual aggregation is not controlled by the user and, worst, it does not give feedbacks regarding the information loss.

Some techniques from graph analysis and data clustering build groups of agents out of their microscopic properties (see for example [14, 11, 7]). Such considerations may meet ours on a theoretical point of view, but the approach presented in this report support a very different philosophy: *abstractions should be built regarding macroscopic semantics.* We claim that, to be meaningful, the aggregation process need to rely on macroscopic concepts from the experts. Hence, our approach should rather be related to researches on multi-level agent-based models [5]. These works openly tackle the abstraction problem by designing MAS on several levels of organization according to expert definitions. Such approaches aim at reducing the computational cost of simulations depending on the expected level of detail. The measures and techniques presented in this report may provide a formal and quantitative framework to such researches.

To conclude, aggregation techniques should be more systematically implemented on MAS platforms in order to handle complex systems. They should combine consistent macroscopic semantics from the experts and feedbacks regarding the abstractions quality. In our experiments, we use geographical aggregates defined by geographers to build meaningful world areas. They are evaluated to define which have the best properties in term of information content.

3 Agent-based Modeling of International Relations

This section presents the GEOMEDIA agent-based model. It consists in the microscopic description of countries with agents and the macroscopic description of world dynamics with groups and organizations.

3.1 Microscopic Data

Let A be a set of agents. It constitutes the MAS microscopic level. Visualization tools aim at displaying and explaining *variables* regarding these agents: their behavior and internal states, the events they are associated with, the messages they exchange, and so on. Given a variable v, the set of values $\{v(a)\}_{a \in A}$ composes the system *microscopic description* (illustrated by distribution P in Fig. 1).

In the GEOMEDIA project, we are interested in the analysis of world international dynamics. The microscopic level of agents contains 168 countries. Information regarding their behavior has been extracted from 70 RSS feeds of English newspapers, from May 2011 to September 2012. Each article that names a country is interpreted as an *event* in the lifetime of the corresponding agent. Each article that simultaneously names two or more countries is also interpreted as a *relation* between the corresponding agents. We thus are interested in two variables: (1) `events_nb`, the weights of agents within news and (2) `relations_nb`, the weights of their relations. Here are the global results for the newspapers used in the following experiments.

	Newspaper	Country	Articles	Events	Relations
`feed_CAN`	Vancouver Sun	Canada	15,011	2,422	376
`feed_GBR`	Daily Mail	UK	43,156	12,911	3,059
`feed_PHL`	Ph. Daily Inquirer	Philippines	18,277	14,205	6,342

3.2 Macroscopic Data

A *group* $G \subset A$ is subset of agents that are members of a coherent organizational pattern. It can be interpreted as an *abstract agent* that sums up the behavior of its underlying agents. Hence, groups satisfy a recursive definition: a group is either an agent or a set of groups. Variables can be defined on a group G in several ways [4], such as: $v(G)$ can be the *sum* of agents values (for *extensive* variables such as events or relations number – see Q' in Fig. 1); or the weighted *mean* of agents values (for *intensive* variables such as events or relations frequency).

We define an *organization* O as a set of groups that constitutes a *partition* of the agents set A. Thus, in the scope of this report, each agent is always a member of one and only one group. The set of group values $\{v(G)\}_{G \in O}$ composes a *macroscopic description* of the system wrt an organization. It simplifies the variable distribution, from the detailed microscopic description (P in Fig. 1) to an aggregated one (Q'). When comparing both descriptions, it is underlined that group values are uniformly distributed over the agents (from Q' to Q). Consequently, as illustrated in Fig. 1, some organizations are more suitable than others for the analysis. For example, using group A seems interesting since P is close to Q, unlike for group B. Hence, organizations should be carefully chosen to provide accurate high-level abstractions. In particular, they should only aggregate homogeneous and redundant distributions. The next section presents a measure to quantify such a property.

In the case of a geographical analysis, groups can be defined according to world topological properties. They thus aggregate close territories. In the following experiments, we consider two hierarchical organizations of world countries, namely `WUTS` [6] and `UNEP` [16]. They define multi-level nested groups that are used by geographers to build global statistics about world areas, from the microscopic level of agents to the full aggregation. `WUTS_5` corresponds to the agent level (Fig. 6) and `WUTS_4`, `WUTS_3` (Fig. 2), `WUTS_2` and `UNEP_region` (Fig. 4), correspond to mesoscopic or macroscopic descriptions.

4 KL Divergence Measures Organizations Quality

Among classical similarity measures, Kullback-Leibler divergence [8] is of high interest because of its interpretation in terms of information. This section shows how it can provide feedbacks regarding the quality of groups and organizations.

4.1 Kullback-Leibler Divergence

KL divergence measures the number of bits of information that one loses by using an approximated distribution Q to encode the events location in the agent space instead of using the detailed source distribution P. In other words, KL divergence estimates the information quantity wasted during the aggregation process. As we assume that group values are uniformly distributed among underlying agents, a group which internal distribution is very homogeneous (group A) will have a low divergence, *i.e.* a low information loss, and reciprocally (group B).

From the KL formula [8], we define *divergence* (or information *loss*) of a group G as follows (more details can be found in [10]):

$$\text{loss}(G) = \sum_{a \in G} \frac{v(a)}{v_0} \times \log_2 \left(\frac{v(a)}{v(G)} \times |G| \right) \tag{1}$$

where v_0 is the sum of all values (*i.e.* the total number of events). KL divergence is thus expressed in bits/event. It verifies the *sum property* [2], meaning that the divergence of disjoint groups is the sum of their divergence. Then, for an organization O, we have: $\text{loss}(O) = \sum_{G \in O} \text{loss}(G)$

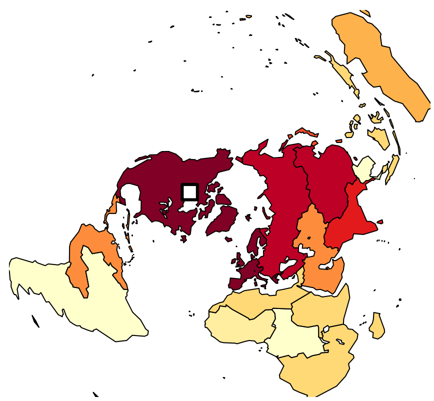
4.2 Groups Quality Depends on the Source of Information

This first experiment aims at showing an essential feature of abstractions: their quality really depends on the context of the analysis. Fig. 2 presents the KL divergence of `WUTS_3` groups according to the three newspapers (for the `events_nb` variable). The darker the groups are, the higher their KL divergence is.

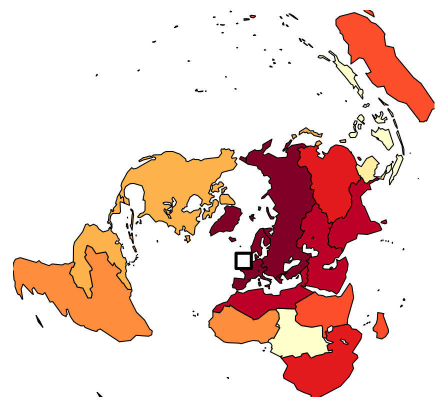
We remark that groups *in which* newspapers are located have high information loss, as for groups that are located *close to* the newspaper (*e.g.* `Eastern Asia` close to Philippines in Fig. 2(c)) or that contain agents that are culturally or politically *related to* the newspaper country (*e.g.* `Southern Africa` related to UK in Fig. 2(b)). This can be explained by the fact that, for a given newspaper, close or related agents may have very divergent behaviors, whereas far agents are more or less the same. We do not aim at proving that such hypotheses are universally verified, but at showing that groups should be chosen with respect to the analyzed dataset. In this case, it straightly depends on the source of the information. As a consequence, if an analyst uses distributed probes to observe a MAS, she does not want to use a unique abstraction pattern to summarize the generated information. This is consistent with the *subjectivist* account of emergence, according to which emergent phenomena strongly relies on the observation process [3].

It can be argued that, in practice, there is a correlation between KL divergence and the events number. Thus, one may want to directly use the `events_nb` variable to identify unsuitable groups. Fig. 2(d) shows that, if it is the case for most groups, some do not satisfy this empirical assumption. For example, in `feed_GBR` articles, the `N. America` group has a surprisingly low KL divergence compared to its events number. To a lower extent, the `E. Europe & N. Asia` group has a higher KL divergence than a linear regression would predict. Henceforth, in practice, events number is not a sufficient criterion for group evaluation.

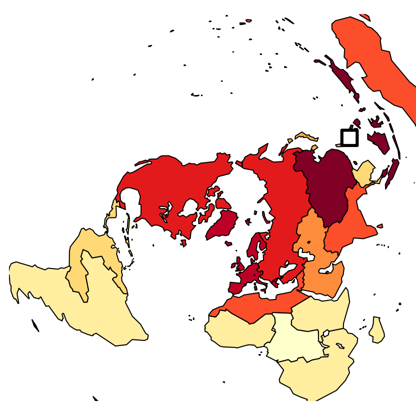
Figure 2: These maps present the spatial variation of KL divergence of `WUTS_3` groups (the darker, the higher) for three newspapers (locations indicated by white squares). The plot shows the result of a linear regression between the number of events and the KL divergence of these groups (for `feed_GBR`).



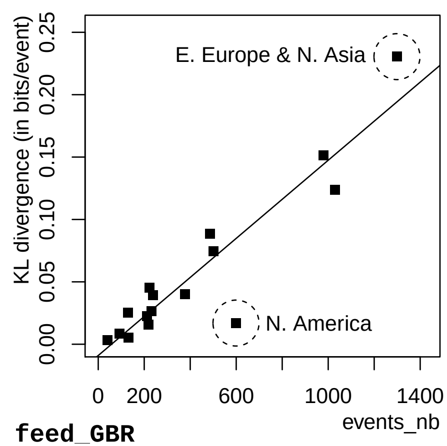
(a) `feed_CAN` (Canada)



(b) `feed_GBR` (UK)



(c) `feed_PHL` (Philippines)

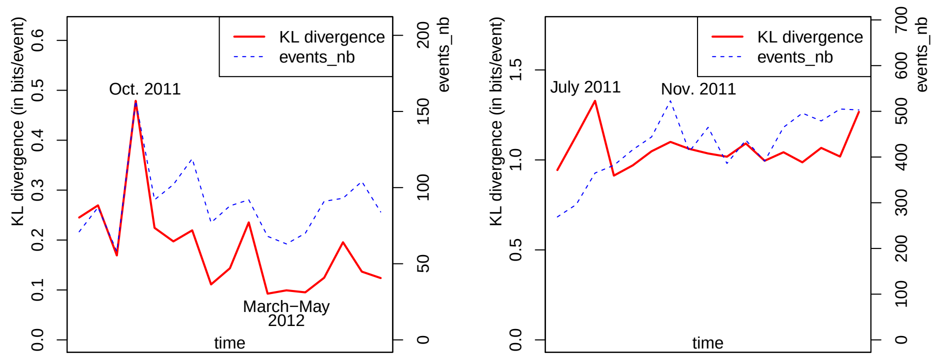


(d) `events_nb` vs. KL divergence

4.3 Groups Quality Depends on Time

As well as depending on the information source, the KL divergence of groups also depends on time. Fig. 3 presents the variation of KL divergence (tick line) and `events_nb` (dashed line) for two `WUTS_2` groups. These values have been computed for each month separately. Fig. 3(a) shows that a group can have a poor quality on specific time periods (*e.g.* Oct. 2011) and high-quality on others (*e.g.* from March to May 2012). Abstractions should then be adapted to the analyzed time period. Fig. 3(b) shows, as previously, that KL divergence is not strictly correlated to the events number (*e.g.* July 2011 and Nov. 2011).

Figure 3: Time variation of the KL Divergence and the events number of two groups from the `WUTS_2` organization, computed on a monthly basis (for `feed_GBR`).



(a) `W. Asia & N. Africa` group (b) `Europe & N. Asia` group

4.4 Comparing Two Organizations

The purpose of this third experiment is to compare two similar agent organizations: `WUTS_2` and `UNEP_region` (see Fig. 4). First, a global comparaison can decide which organization is the *best* according to KL divergence.

	`feed_CAN`	`feed_GBR`	`feed_PHL`
`WUTS_2`	1.80 bits/event	1.46 bits/event	2.07 bits/event
`UNEP_region`	1.57 bits/event	1.51 bits/event	2.26 bits/event

It appears that, for both `feed_GBR` and `feed_PHL`, the sum of groups divergence is slightly lower for `UNEP_region` than for `WUTS_2`. Hence, if one should choose between these two organizations, `UNEP_region` should be preferred (it leads to less information loss). However, for `feed_CAN`, `WUTS_2` is better. Once again, abstractions should be chosen according to the source of information.

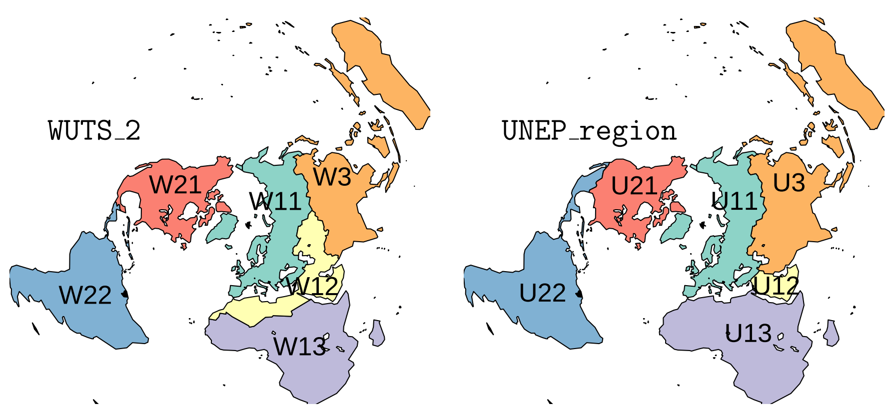
One can perform a more subtle analysis in order to determine the groups best shapes. For example, we notice that $\texttt{U22} = \texttt{W22} \cup \texttt{Mexico}$ and $\texttt{W21} = \texttt{U21} \cup \texttt{Mexico}$ (Fig. 4). Hence, one can ask: What is the best location of the `Mexico` agent? Should it be aggregated with the `Northern America` group (`X21`) or with the `Latin America` one (`X22`)? For `feed_GBR`, we have:

$$\mathrm{loss}(\texttt{W21}) + \mathrm{loss}(\texttt{W22}) = 0.0481 < 0.0547 = \mathrm{loss}(\texttt{U21}) + \mathrm{loss}(\texttt{U22})$$

Thus, the events number of the `Mexico` agent is closer to those of `Northern America` agents. It should be grouped accordingly. This technique allows to evaluate and choose the shape of abstractions used by the experts.

For any pair of disjoint groups G_1 and G_2, we have: $\mathrm{loss}(G_1 \cup G_2) > \mathrm{loss}(G_1) + \mathrm{loss}(G_2)$. This means that, if we only rely on KL divergence, the more precise is always the better: `Mexico` should not be aggregated. Hence, we need a measure that expresses what one *gains* with aggregation.

Figure 4: Two organizations of the agents space in six similar (but not equivalent) groups: locations of the N. African agents, the W. Asian agents and the `Mexico` agent differ.



5 Complexity Reduction of Organizations

The *information loss* criterion presented in the previous section is not sufficient to chose the right level of organization. This section presents two measures of *complexity reduction* to express the *gain* of aggregation. Such measures estimate the information quantity that one saves by representing a group G instead of its underlying agents: $\mathrm{gain}(G) = \left(\sum_{a \in G} Q(a)\right) - Q(G)$, where Q estimates the quantity of information needed to represent an agent or a group.

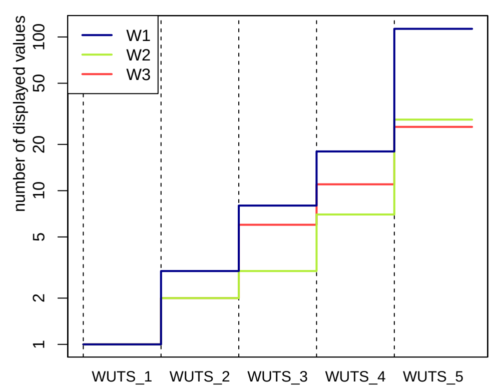
5.1 Number of Encoded Values

One way of measuring information quantities consists in estimating the number of bits needed to encode the values of a given description. We suppose that it is constant for each agent a and group G: $Q(a) = Q(G) = q$, where q depends on the data type of the encoded values. Hence, for a group G, we have: $\mathrm{gain}(G) = (|G| - 1) \times q$. It is a basic complexity measure, but it fits well classical visualizations (as for the maps of this report) since the number of displayed groups $|G|$ defines the granularity of the visualization.

For example, according to the map expected complexity, the user can determine the number of groups that should be displayed. Fig. 5(a) gives the number of groups and the associated gain for each level of the `WUTS` hierarchy. However, all groups do not contain the same number of agents. Fig. 5(b) gives, for each level, the size of `W1`, `W2` and `W3` (see `WUTS_1` in Fig. 6).

Figure 5: Complexity reduction (number of encoded values) for levels of the `WUTS` hierarchy and for `W1`, `W2` and `W3`: the three high-level groups of `WUTS_1` (see Fig. 6).

Level	Values nb.	gain/q
`WUTS_0`	1	167 bits
`WUTS_1`	3	165 bits
`WUTS_2`	7	161 bits
`WUTS_3`	17	151 bits
`WUTS_4`	36	132 bits
`WUTS_5`	168	0 bit



The user may want to adapt these groups levels depending on the amount of detail she expects for the corresponding world areas. The following section presents a criterion that automatically combines KL divergence and complexity reduction to adapt the size of groups depending on their quality, thus leading to multi-resolution organizations.

5.2 Shannon Entropy

The number of values only depends on the groups topology. To the contrary, Shannon entropy also depends on the variable distribution. It is a classical complexity measure that is consistent with KL divergence (it can be defined as *the divergence from the uniform distribution* [8]). Briefly, entropy evaluates the information quantity needed to encode the location of *each event* within the agent space (and not only the value of *each agent*). From Shannon formula [13], we defined the *entropy reduction* (or *gain*, in bits/event) of a group G as follows:

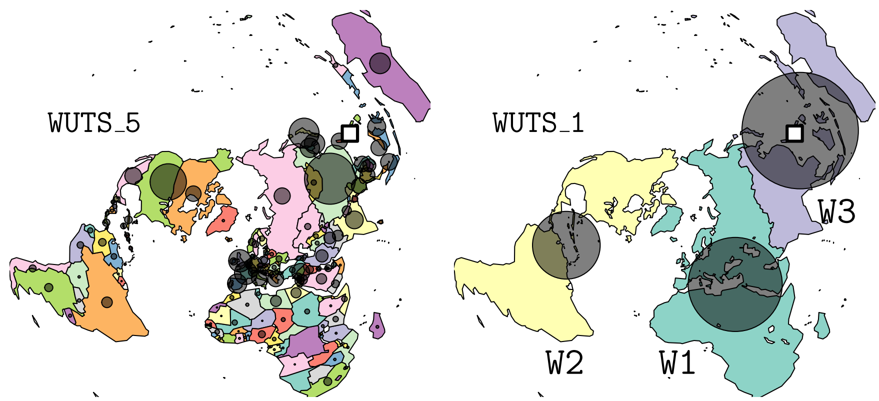
$$\mathrm{gain}(G) = \left(\frac{v(G)}{v_0}\log_2\left(\frac{v(G)}{v_0}\right)\right) - \sum_{a \in G}\left(\frac{v(a)}{v_0}\log_2\left(\frac{v(a)}{v_0}\right)\right) \qquad (2)$$

The choice of either one or the other complexity measure depends on the performed analysis. *Shannon entropy* is more adapted to the visualization of individuated events or relations, whereas *the number of values* is more adapted to the visualization of aggregated values. In any case, techniques presented in this report are meant to be generic. They can be used with any complexity measure as long as it fits some algebraic properties (see [10] for more details).

6 Multi-resolution Organizations of MAS

As a conclusion to the previous sections, finding a *good* organization relies on two issues. (1) What *gain* is provided by the aggregation of agents into an average behavior? (2) What *loss* is induced by such an aggregation? Choosing an organization thus consists in finding a compromise between a complexity reduction and an information loss. Fig. 6 shows two organizational levels: One that preserves all details (low loss and low gain) and the other that roughly aggregates in three groups (high gain and high loss). Obviously, we need to strike a balance.

Figure 6: Two very different levels of organization for `feed_PHL`. Circle areas are proportional to the `events_nb` variable (value of the `Philippines` agent is not displayed).



6.1 Parametrized Information Criterion

A *parametrized Information Criterion* can express the trade-off between complexity reduction and KL divergence for a given group G:

$$\mathrm{pIC}(G) = p \times \mathrm{gain}(G) - (1 - p) \times \mathrm{loss}(G) \tag{3}$$

where $p \in [0, 1]$ is a parameter used to balance the trade-off. For $p = 0$, maximizing the pIC is equivalent to minimizing the loss: the user wants to be the more precise (microscopic level). For $p = 1$, she wants to be the simpler (full aggregation). When p varies from 0 to 1, a whole class of nested organizations arises. The analyst has to chose the ones that fulfill her requirements: between the expected amount of details and the available computational resources.

Fig. 7 presents such a two-dimensional evaluation of `WUTS_3` groups. By comparing KL divergence and entropy reduction, one can easily spot groups that have a good gain/loss ratio. The more a group is closed to the bottom-left corner, the more its complexity reduction compensates its information loss, whereas top-right groups have an poor gain/loss ratio and should not be aggregated.

Figure 7: Comparison of entropy reduction and KL divergence (on logarithmic scales) for groups of `WUTS_3` (`feed_PHL`).

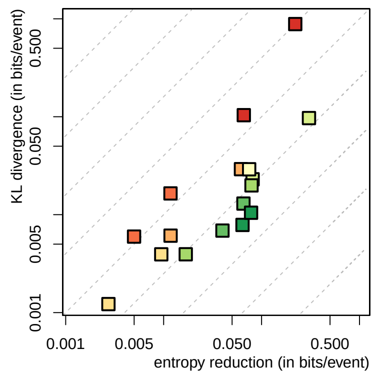
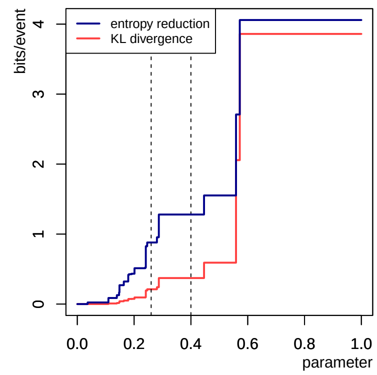


Figure 8: The variation of best organizations KL divergence and entropy reduction as p varies from 0 to 1.



6.2 Organizations within a Hierarchy

Given a value of p, *best* organizations are those that maximize the information criterion. Clustering techniques, using *gain* and *loss* measures as distances, could find such optimal partitions. However, results may have very few meaning since agents would be aggregated regardless of their location within the system. Moreover, we generally assume a correlation between topology and behavior. Hence, we claim that, to be meaningful, organizations should fit topological constraints.

In this subsection, we are interested in hierarchically organized MAS. A *hierarchy* H is a set of nested groups, defined from the microscopic level (each agent is a group) to the whole MAS (only one group). The number of possible multi-resolution organizations within such a hierarchy *exponentially* depends on the number of levels. For `UNEP` (3 levels) and `WUTS` (5 levels), we respectively have 1.3×10^6 and 3.8×10^{12} possible organizations. Finding the best one can thus be computationally expensive. Algorithm 1 below finds topologically-consistent organizations that maximize our information criterion. It *linearly* depends on the number of groups in the hierarchy (respectively 196 and 231 groups) by processing a classical linear search within the branches of the hierarchy. Indeed, according to the *sum property* [2] of our information-theoretic measures (see subsection 4.1), each branch can be independently evaluated.

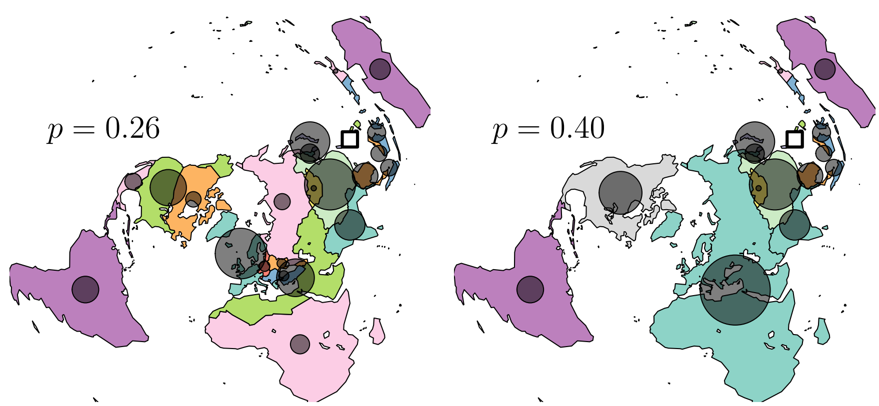
Algorithm 1 linearly finds best organizations within a hierarchy

Require: A hierarchy H and a trade-off parameter p in $[0, 1]$.
Ensure: An organization made of groups in H and maximizing pIC.

procedure FINDBESTORGANIZATION(H, p)
  $G \leftarrow$ biggest group of H
  if H contains only one group G **then** **return** $\{G\}$
  for each S direct subhierarchies of H **do**
    $aux \leftarrow$ FINDBESTORGANIZATION(S, p)
    $bestOrganization \leftarrow$ UNION($bestOrganization, aux$)
  if pIC of $\{G\} > pIC$ of $bestOrganization$ **then return** $\{G\}$
  else return $bestOrganization$

This algorithm has been executed on the `WUTS` hierarchy for `feed_PHL`. As we increase the gain/loss parameter p, complexity decreases and divergence increases (see Fig. 8). For $p = 0$, all agents are displayed (see Fig. 6). This map is hard to read because to much (redundant) information is displayed (*e.g.* in Western Europe). Maps in Fig. 9 present the best organizations for two higher values of p. For $p = 0.26$, some groups are aggregated (*e.g* `Latin America` and `S. Africa`). They correspond to the groups in Fig. 2(c) that have a very low KL divergence. Other ones, that have a high information loss wrt their complexity reduction, are kept detailed. As p increases, higher-level groups are displayed, thus reducing the map complexity while saving the more information. This technique leads to multi-resolution maps that fit the variable distribution. For $p > 0.56$, only the total number of events is displayed (full aggregation).

Figure 9: Two multi-resolution organizations within `WUTS` hierarchy for different values of the trade-off parameter p (see dashed lines in Fig. 8).



7 Conclusion and Perspectives

The design and debugging of complex MAS need abstraction tools to work at a higher level of description. However, such tools have to be build and exploited with the greatest precaution in order to preserve useful information regarding the system behavior and to guaranty that generated descriptions are not misleading. To that extent, this report focuses on aggregation techniques for large-scale MAS and give tracks to estimate their quality in term of information content. They are applied to the geographical aggregation of international relations through the point of view of on-line newspapers. We show that, by combining information theoretic measures, one can give interesting feedbacks regarding geographical abstractions and build multi-resolution maps of the world that adapt the visualization complexity to the effective information content.

Future work will apply these techniques to other dimensions of the analysis: *e.g.* for temporal aggregation, thematic aggregation, multi-dimensional aggregation, and so on. Besides this work, we are currently exploiting these tools for performance visualization of large-scale distributed systems [9]. This kind of application shows that our techniques can be scaled up to 1 million agents.

Acknowledgement

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References

[1] L. Búrdalo, A. Terrasa, V. Julián, and A. García-Fornes. A Tracing System Architecture for Self-adaptive Multiagent Systems. In Y. Demazeau, editor, *8th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS'10), University of Salamanca, Spain*, pages 205–210, 2010.

[2] I. Csiszár. Axiomatic Characterizations of Information Measures. *Entropy*, 10(3):261–273, 2008.

[3] J. Deguet, Y. Demazeau, and L. Magnin. Element about the Emergence Issue: A Survey of Emergence Definitions. *ComPlexUs*, 3:24–31, 2006.

[4] N. Elmqvist and J. Fekete. Hierarchical Aggregation for Information Visualization: Overview, Techniques, and Design Guidelines. *IEEE Transactions on Visualization and Computer Graphics*, 16(3):439–454, 2010.

[5] J. Gil-Quijano, T. Louail, and G. Hutzler. From Biological to Urban Cells: Lessons from Three Multilevel Agent-Based Models. In N. Desai, A. Liu, and M. Winikoff, editors, *Principles and Practice of Multi-Agent Systems*, volume 7057 of *Lecture Notes in Computer Science*, pages 620–635. Springer Berlin Heidelberg, 2012.

[6] C. Grasland and C. Didelon. *Europe in the World – Final Report. Volume 1 of ESPON Project 3.4.1*, volume 1. ESPON, 2007.

[7] P. Iravani. Multi-level network analysis of multi-agent systems. In *RoboCup 2008: Robot Soccer World Cup XII (LNAI)*, volume 5399 of *Lecture Notes in Computer Science*, pages 495–506. Springer-Verlag, 2009.

[8] S. Kullback and R. Leibler. On Information and Sufficiency. *Annals of Mathematical Statistics*, 22(1):79–86, 1951.

[9] R. Lamarche-Perrin, L. M. Schnorr, J.-M. Vincent, and Y. Demazeau. Evaluating Trace Aggregation Through Entropy Measures for Optimal Performance Visualization of Large Distributed Systems. In *The 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (submitted)*, 2012.

[10] R. Lamarche-Perrin, J.-M. Vincent, and Y. Demazeau. Informational Measures of Aggregation for Complex Systems Analysis. Technical Report RR-LIG-026, Laboratoire d'Informatique de Grenoble, 2012.

[11] W. Peng, A. Grushin, V. Manikonda, W. Krueger, P. Carlos, and M. Santos. Graph-Based Methods for the Analysis of Large-Scale Multiagent Systems. In K. S. Decker, J. S. Sichman, C. Sierra, and C. Castelfranchi, editors, *8th International Conference on Autonomous Agents and Multiagent Systems (AAMAS'09), Budapest, Hungary*, pages 545–552. International Foundation for Autonomous Agents and Multiagent Systems, 2009.

[12] S. F. Railsback, S. L. Lytinen, and S. K. Jackson. Agent-based Simulation Platforms: Review and Development Recommendations. *Simulation*, 82:609–623, 2006.

[13] C. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423,623–656, 1948.

[14] A. Sharpanskykh and J. Treur. Group Abstraction for Large-Scale Agent-Based Social Diffusion Models with Unaffected Agents. In D. Kinny, J.-J. Hsu, G. Governatori, and A. K. Ghose, editors, *Agents in Principle, Agents in Practice*, volume 7047 of *Lecture Notes in Computer Science*, pages 129–142. Springer Berlin Heidelberg, 2011.

[15] J. Tonn and S. Kaiser. ASGARD – A Graphical Monitoring Tool for Distributed Agent Infrastructures. In Y. Demazeau, editor, *8th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS'10), University of Salamanca, Spain*, pages 163–175, 2010.

[16] United Nations Environment Programme. *Global Environmental Outlook (GEO-4): environment for development*, volume 4. UNEP, Nairobi, 2007.

[17] M. H. Van Liedekerke and N. M. Avouris. Debugging multi-agent systems. In *Information and Software Technology*, volume 37, pages 103–112, 1995.